

# Artificial Intelligence

## Chapter -15



<https://xkcd.com/329/>



# LEARNING OBJECTIVES

- Describe the two types of artificial intelligence
- Explain the pros and cons of various knowledge representation methods
- Explain the parts of a simple neural network, how it works, and how it can incorporate machine learning



# INTRODUCTION

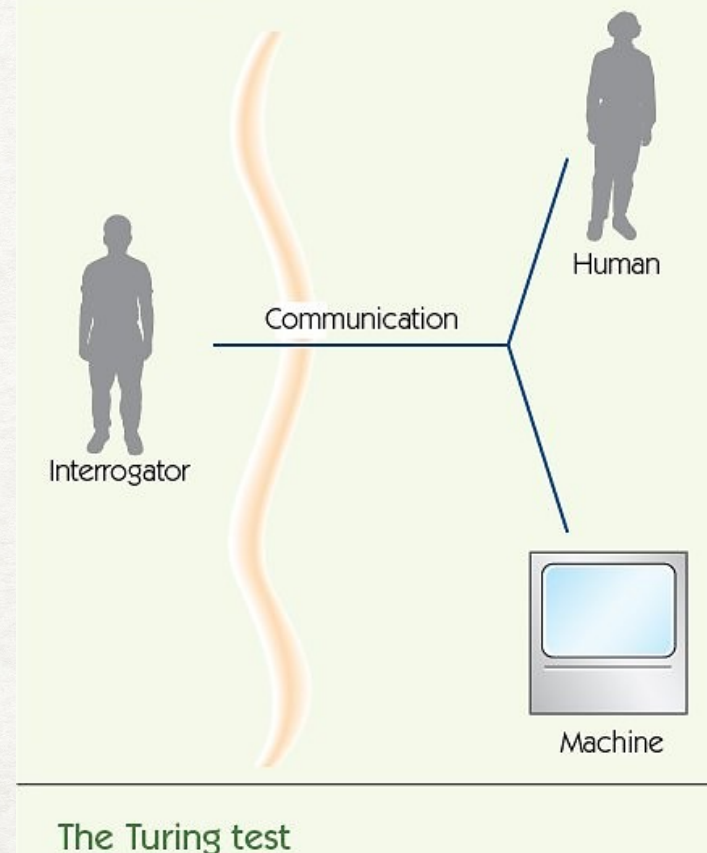
**Artificial Intelligence (AI):** creating computer systems that exhibit aspects of human intelligence.

What is intelligence?

The **Turing Test** (by Alan Turing 1950)

- Human judge questions two hidden entities
  - One entity is a person
  - One entity is a computer
- If the judge cannot distinguish the computer's response from the person's more than half the time, then the computer is intelligent!

FIGURE 15.1






# REVERSE TURING TEST

The computer administers a test to determine if the subject is human or not.

Please check the box below to proceed.

☐ I'm not a robot

  
reCAPTCHA  
[Privacy](#) - [Terms](#)



Type the characters above:

Go

CAPTCHA - Completely Automated Public Turing  
Test to tell Computers and Humans Apart



# PROBLEMS WITH THE TURING TEST

- One counter argument – the Chinese room argument was put forward by John Searle in 1980.



Image source:

<https://theness.com/neurologicablog/index.php/ai-and-the-chinese-room-argument/>

1. Get Chinese symbols as inputs.
  2. Look at a rule book in native language.
  3. Output a symbol based on the rules.
- Somebody outside the room might think that what/who is inside the room understand Chinese.
- Passing the Turing test does not mean the computer “understands” what it is doing + It is limited to the natural language skills.
  - Questions the nature of intelligence and the definition of artificial intelligence.
  - Topic still debated by scientists and philosophers nowadays.

<https://www.ibm.com/cloud/learn/strong-ai>



# WINOGRAD SCHEMA CHALLENGE

(NAMED AFTER TERRY WINOGRAD)

This test proposed giving a statement to the machine that could not be interpreted properly unless the machine had the sort of experience and understanding a human being has.

A Winograd Schema Challenge consists of a statement and a question.

The statement must contain  
two *entities* and  
an ambiguous *pronoun*  
that could, refer to either of the two entities.

The question asks which of the entities the pronoun refers to and must require some sort of *world knowledge* and *reasoning* for its resolution, (what is common sense for us).



# WINOGRAD SCHEMA CHALLENGE : EXAMPLES

1. The city councilmen refused the demonstrators a permit because *they* feared violence.

The city councilmen refused the demonstrators a permit because *they* advocated violence.

Question to the machine: *Who does "they" refer to?*

2. Alice moved in with Berta when *she* had a spare room in her flat.  
Alice moved in with Berta when *she* had a moldy room in her flat.

Question to the machine: *Who does "she" refer to?*

3. The policeman arrested the offender after *he* had seen the evidence.  
The policeman arrested the offender after *he* had hidden the evidence.

Question to the machine: *Who does "he" refer to?*

A collection of 150 Winograd schemas

<https://cs.nyu.edu/faculty/davise/papers/WinogradSchemas/WSCollection.html>



# A DIVISION OF LABOR

We can divide the types of tasks we as humans can do into 3 broad categories:

## 1. Computational tasks

- Adding a column of numbers
- Sorting a list of numbers
- Managing a payroll
- Calculating the trajectory of a space shuttle

## 2. Recognition tasks

- Recognizing your best friend
- Understanding the spoken word
- Finding a tennis ball in the grass

## 3. Reasoning tasks

- Planning what to wear today
- Deciding on your courses for the next semester
- Running the triage center in a hospital after an emergency



# A DIVISION OF LABOR

We can divide the types of tasks we as humans can do into 3 broad categories

## 1. Computational tasks

- Typically have algorithmic solutions
- Computers perform them faster than humans
- Computers perform them more accurately than humans

## 2. Recognition tasks

Example: recognizing an individual's face

## 3. Reasoning tasks

Example: planning your major in college



# A DIVISION OF LABOR

We can divide the types of tasks we as humans can do into 3 broad categories

1. Computational tasks
2. Recognition tasks : (e.g. recognizing an individual's face)
  - Process massive amounts of sensory information
  - Access massive amounts of past experience
  - Require generalisation of knowledge
  - Humans are often better than computers
3. Reasoning tasks  
Example: planning your major in college



# A DIVISION OF LABOR

We can divide the types of tasks we as humans can do into 3 broad categories :

1. Computational tasks

2. Recognition tasks

Example: recognizing an individual's face

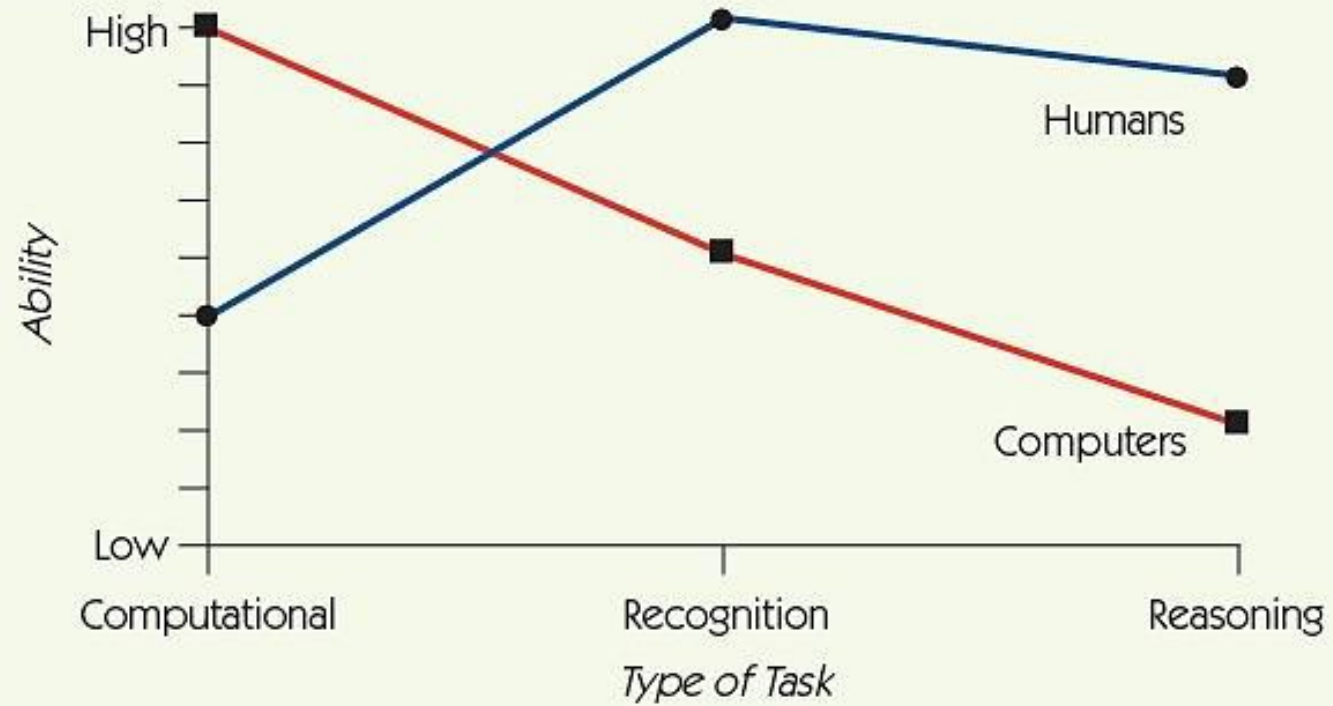
3. Reasoning tasks

- Reasoning tasks require accessing memory, as well as cause and effect information.
- **Formal reasoning** can be automated to some extent
  - Problems become intractable quickly
- **Informal reasoning** or Common-sense reasoning
  - Requires great experience and knowledge



# A DIVISION OF LABOR

**FIGURE 15.2**



Human and computer capabilities



# HOW CAN WE REPRESENT KNOWLEDGE FOR THE COMPUTER?

Two common ways of storing knowledge in a computer are *formal languages* and *semantic nets*.

**Formal languages** are in principle like natural languages, but with a generally much simpler grammar and a lot less potential for ambiguity.

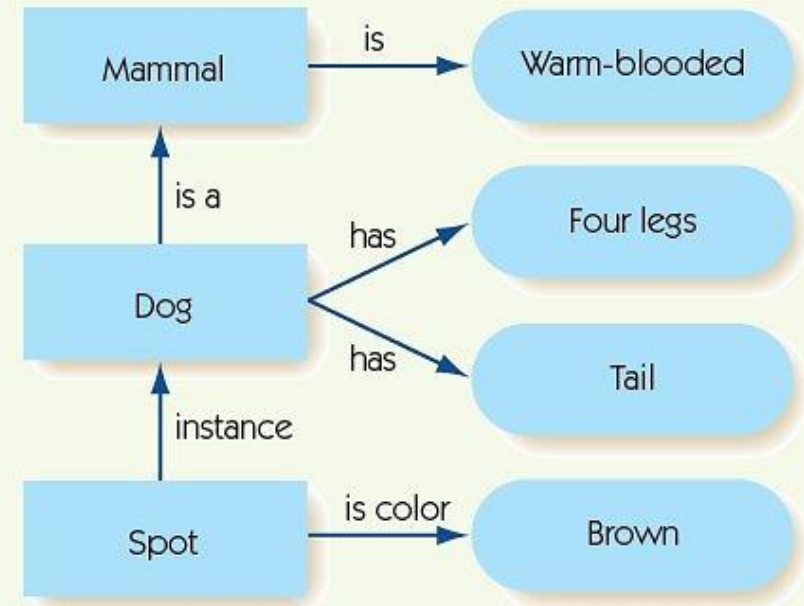
Natural Language Statement	Symbolic Representation
Spot is a dog.	$dog(Spot)$
Spot is brown.	$brown(Spot)$
Every dog has four legs	$(\forall x) (dog(x) \rightarrow four-legged(x))$
Every dog has a tail	$(\forall x) (dog(x) \rightarrow tail(x))$
Every dog is a mammal	$(\forall x) (dog(x) \rightarrow mammal(x))$
Every mammal is warm-blooded	$(\forall x) (mammal(x) \rightarrow warm-blooded(x))$



# KNOWLEDGE REPRESENTATION

- Graphical representation
  - Aka **Semantic net**
    - Nodes for objects or categories of objects
    - Edges for relationships
    - Nodes inherit features through “is-a” relationships

FIGURE 15.3



A semantic net representation

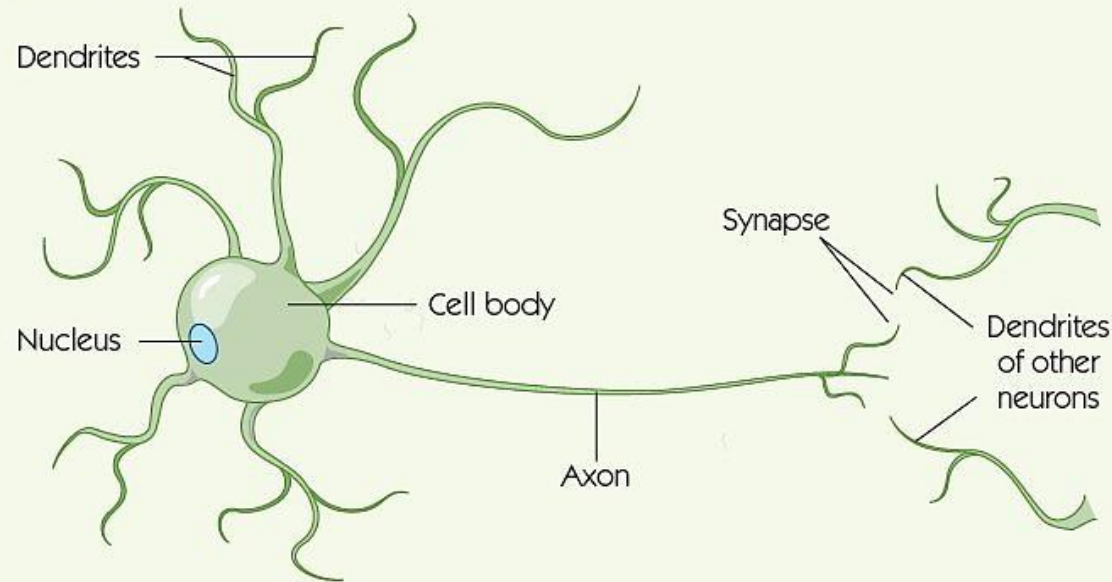


# MIMICKING A SIMPLIFIED VERSION OF THE BRAIN

To make computers “learn” and “think” like humans, it is natural to mimic the way the human brain functions.

Human brain contains about 86 billion ( $10^{12}$ ) neurons, which are like very simple computational devices.

**FIGURE 15.4**



A neuron



# ARTIFICIAL NEURAL NETWORK (ANN)

The human brain can be seen as a **connectionist architecture**.

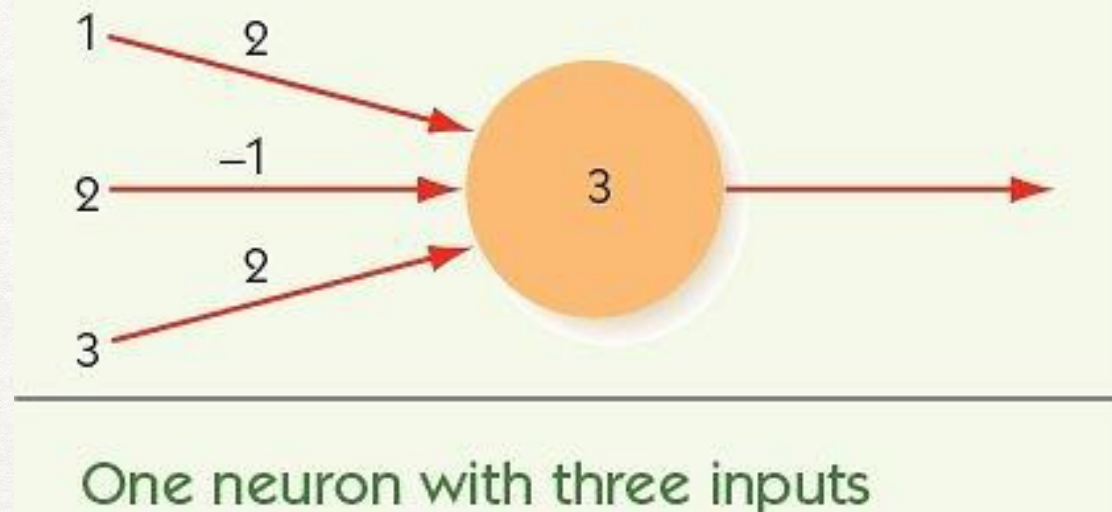
Artificial **neural networks** mimic this approach.

Neural networks are often used in recognition tasks as they can “learn” from training input.

Individual artificial “neurons” have:

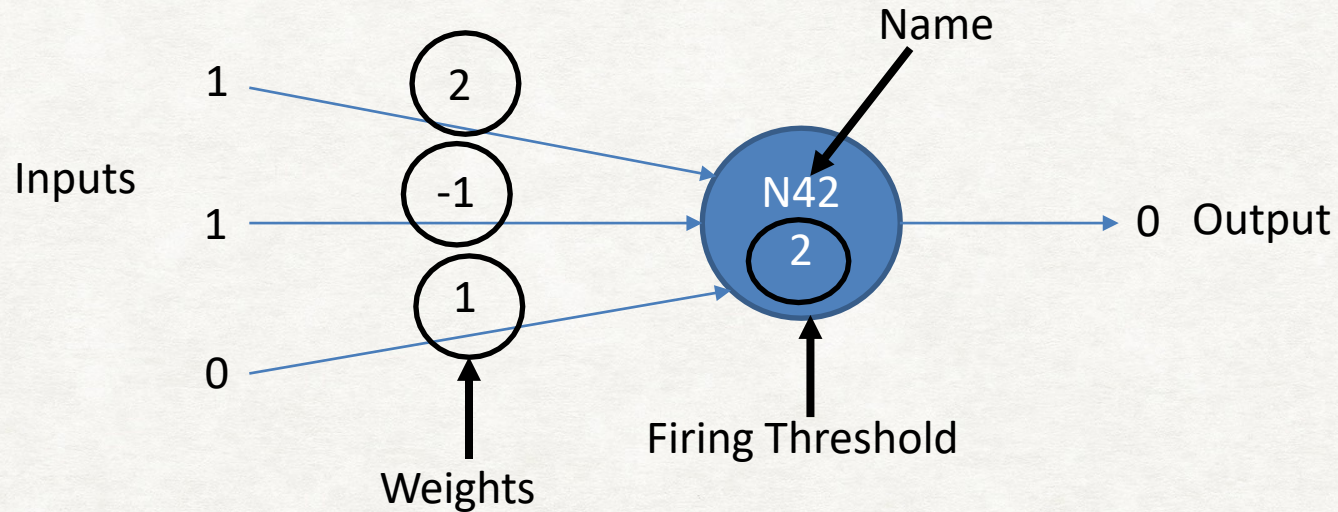
- Incoming weighted edges
- An activation level (threshold or more complicated functions)
- Outgoing weighted edge

**FIGURE 15.5**





# ARTIFICIAL NEURONS



Each input is fed an *input value* 0 or 1.

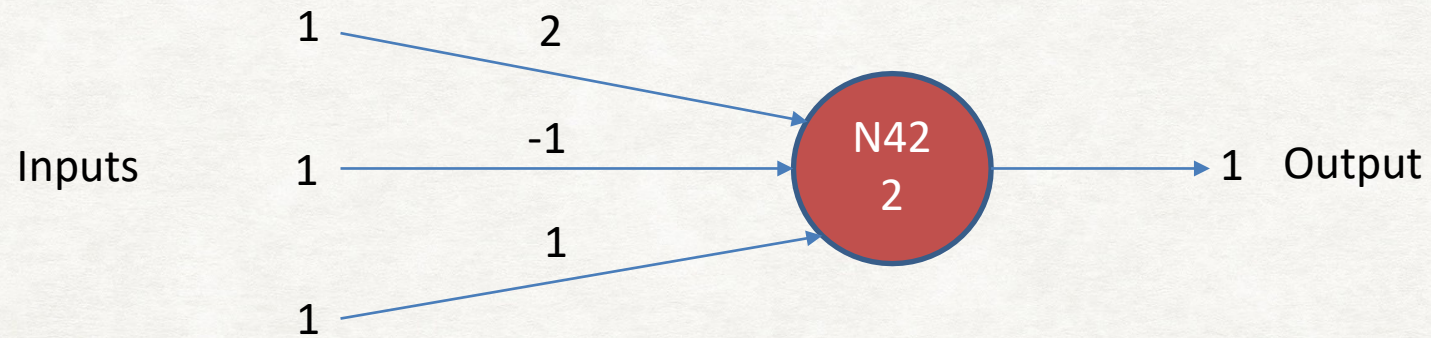
This value is multiplied with the weight and the results are added over all inputs to the neuron.

Here:  $1 * 2 + 1 * (-1) + 0 * 1 = 1$

If the result reaches the firing threshold, then the neuron fires. Here it doesn't.



# ARTIFICIAL NEURONS

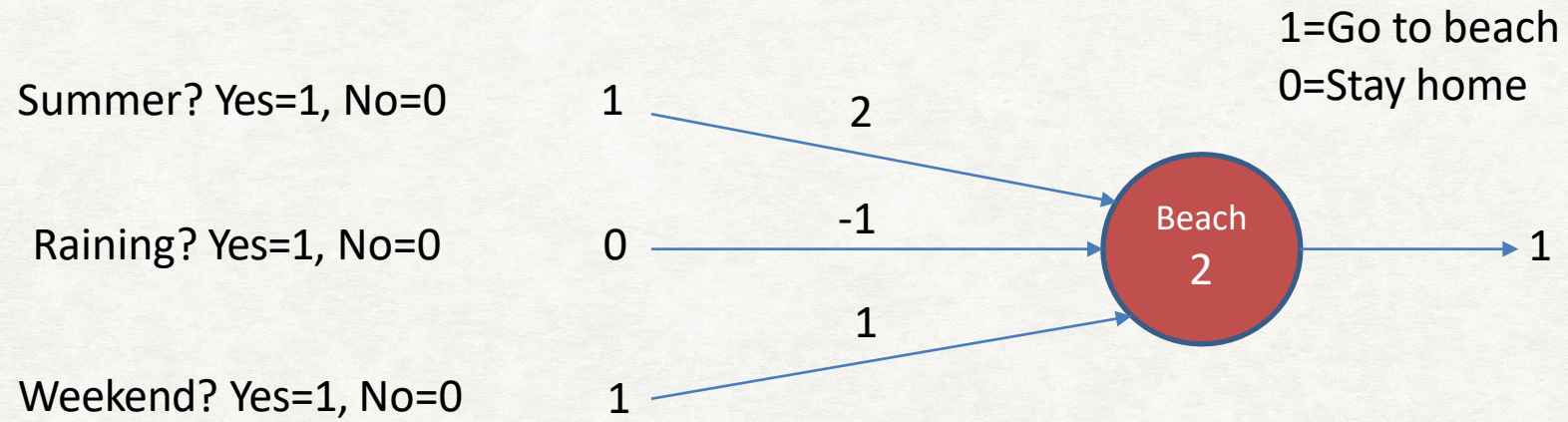


Here, our last input has changed:  $1 * 2 + 1 * (-1) + 1 * 1 = 2$

Now the neuron fires.



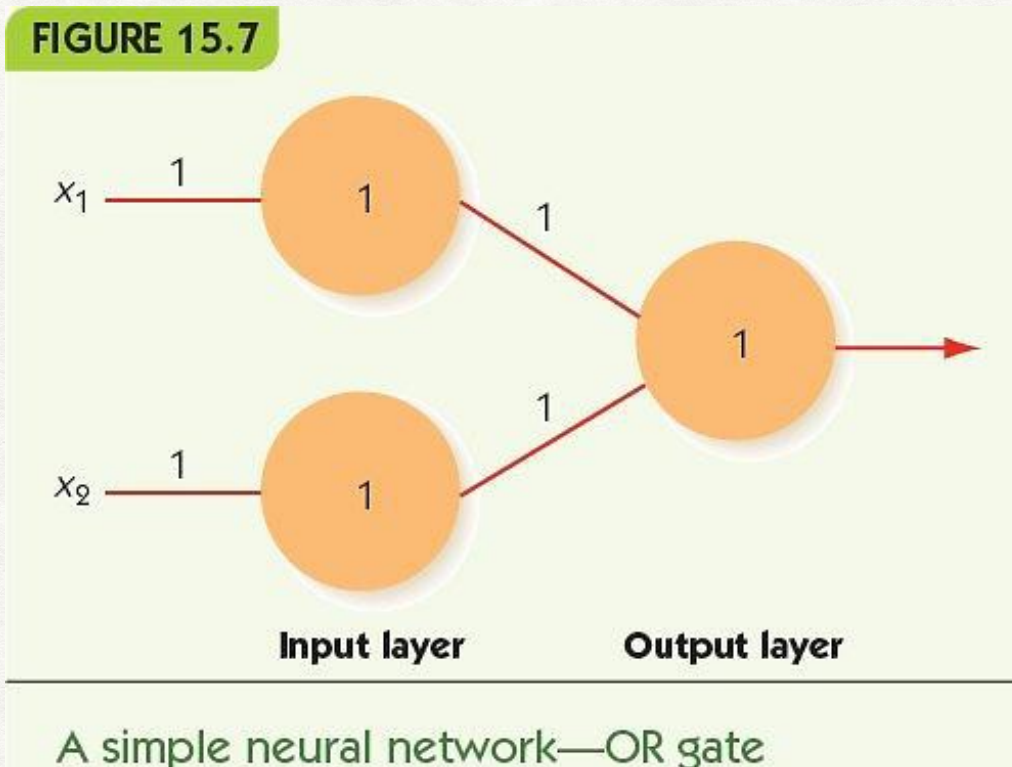
# NEURON DECISION-MAKING EXAMPLE





# ARTIFICIAL NEURAL NETWORK (ANN)

FIGURE 15.7



x1	x2	Output
0	0	0
0	1	1
1	0	1
1	1	1



# ARTIFICIAL NEURAL NETWORK (ANN)

Networks with only one input and output layers:

Can solve many problems, but not all

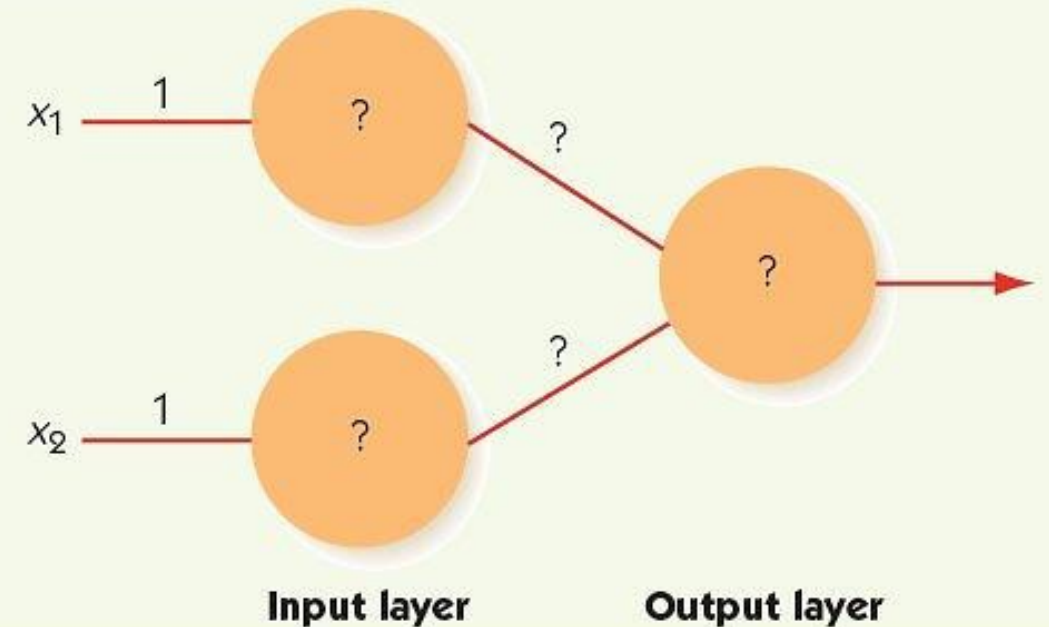
For, example consider the XOR operation

**FIGURE 15.8**

Inputs		Output
$X_1$	$X_2$	
0	0	0
1	0	1
0	1	1
1	1	0

The truth table for XOR

**FIGURE 15.9**



An attempt at an XOR network

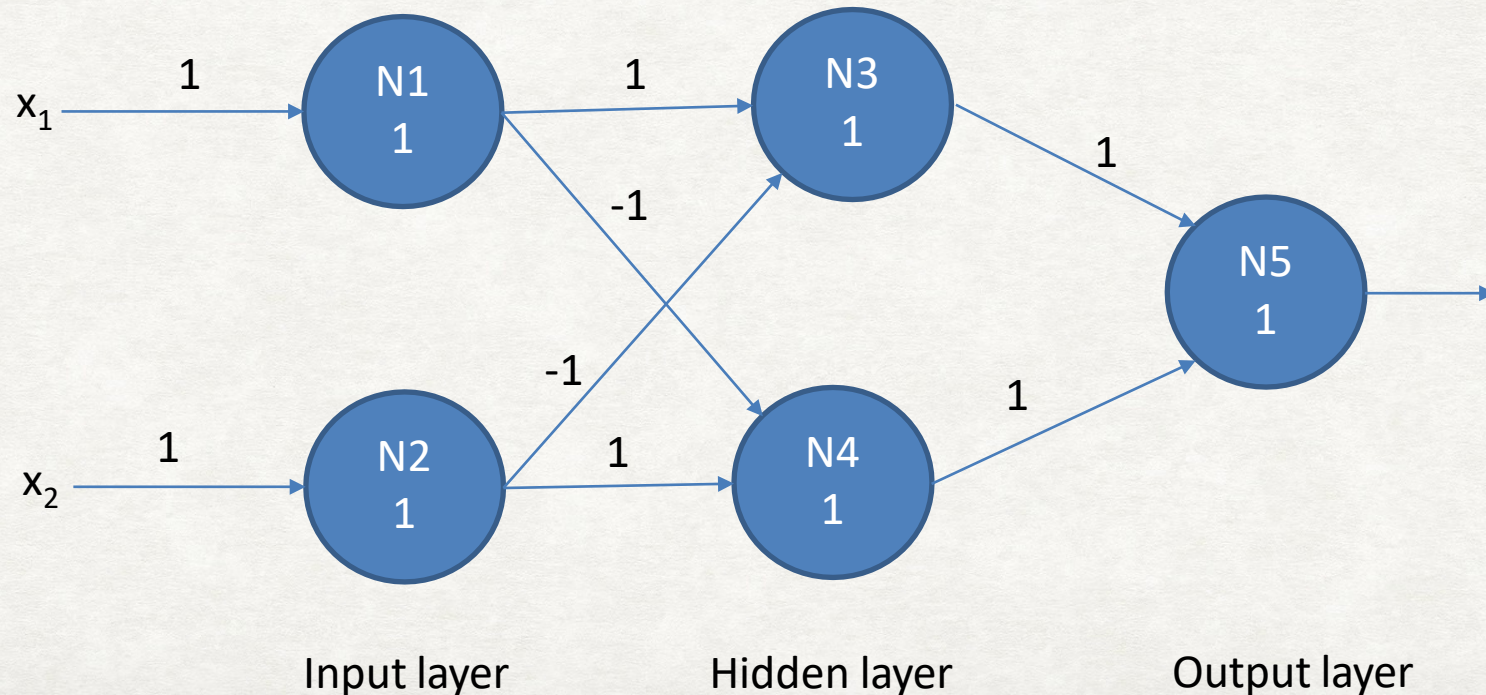


# HIDDEN LAYER IN NEURAL NETWORKS

Add an intermediate layer between input and output

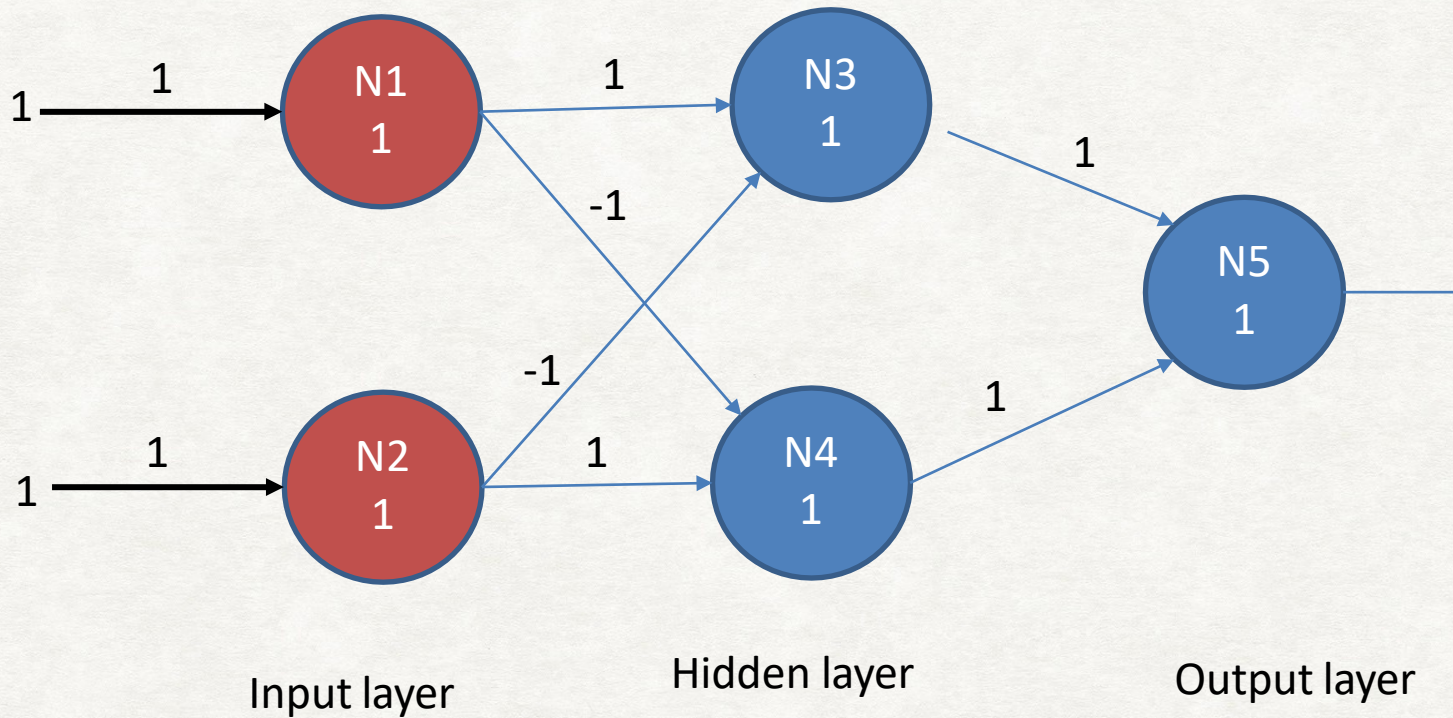
- Hidden layer

Can solve most problems given the right weights and the number of neurons in the hidden layer.





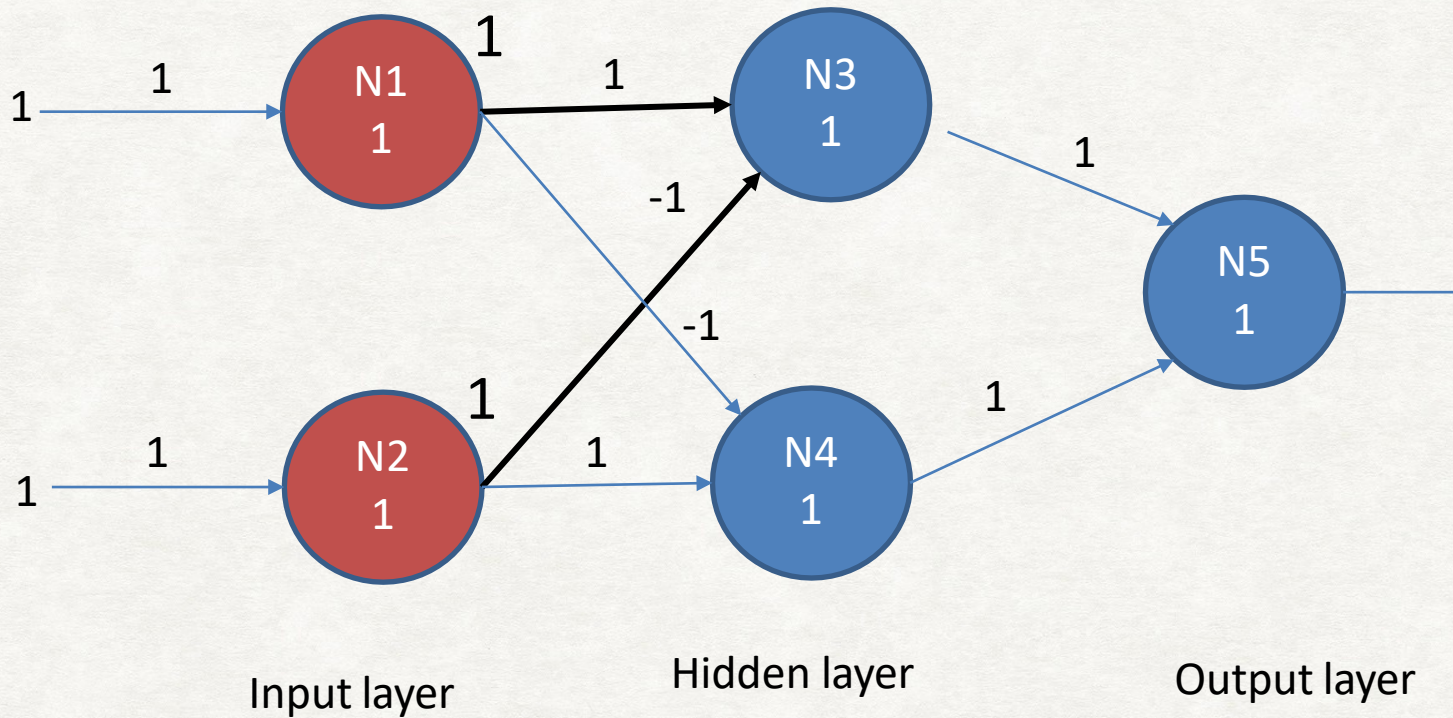
# HIDDEN LAYER IN NEURAL NETWORKS



Neurons N1 and N2 will fire.



# HIDDEN LAYER IN NEURAL NETWORKS

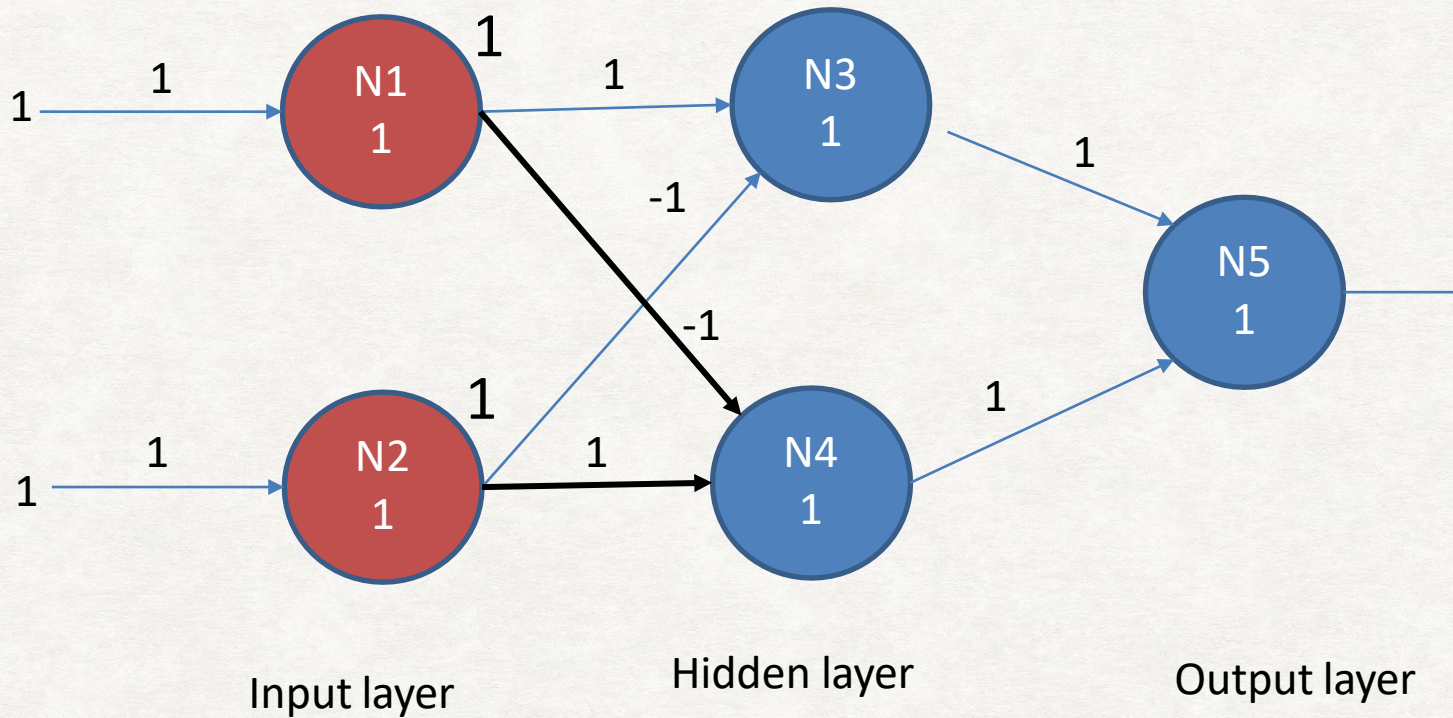


Neurons N3 will not fire.

Input N3 =  $1 + (-1) = 0 < 1$  (threshold of the neuron)



## Hidden Layer in Neural Networks

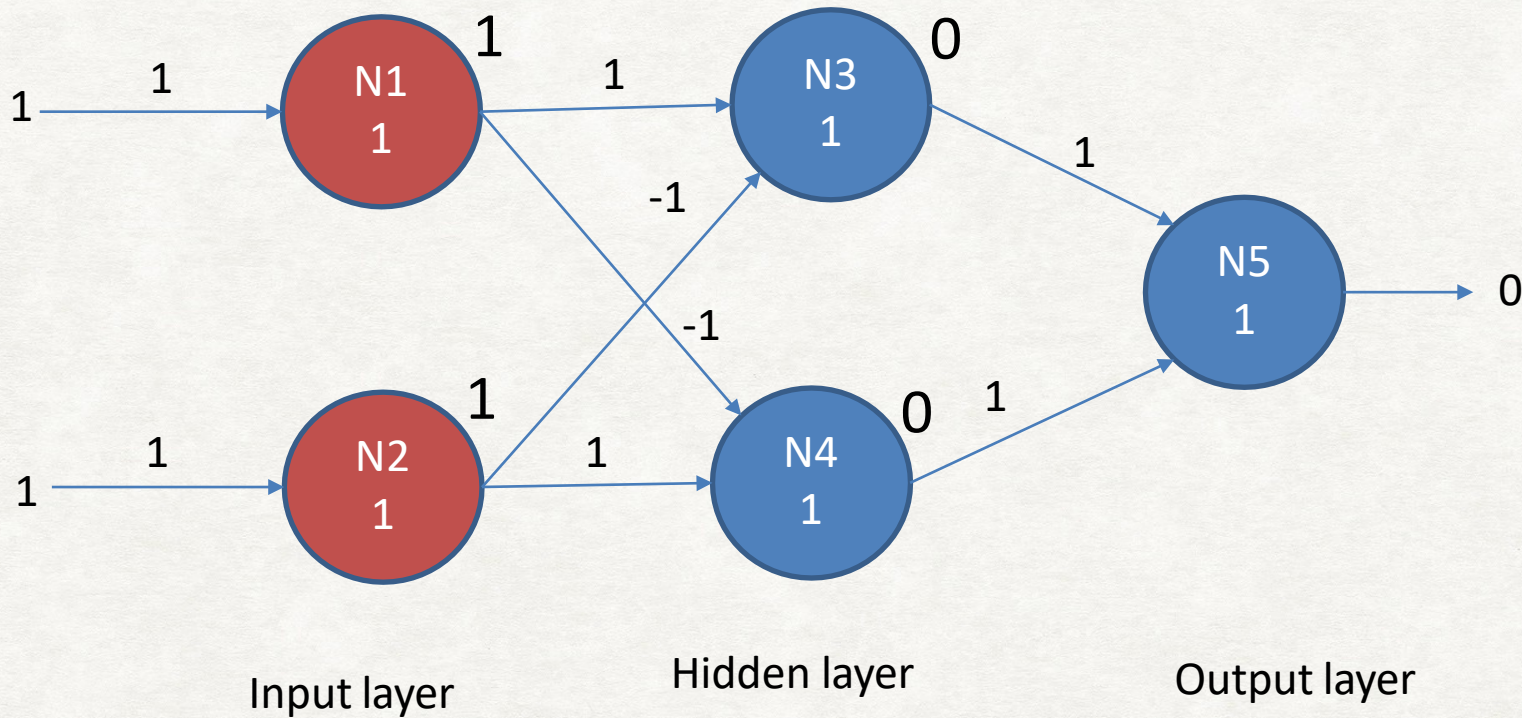


Neurons N4 will not fire.

Input to N4 =  $1 + (-1) = 0 < 1$  (threshold of the neuron)



## Hidden Layer in Neural Networks



Input to neuron N5 =  $0 \cdot 1 + (0 \cdot 1) = 0 < 1$  (threshold of the neuron)

Neuron N5 will not fire.

Output will be 0, as needed. ( $1 \oplus 1 = 0$ )



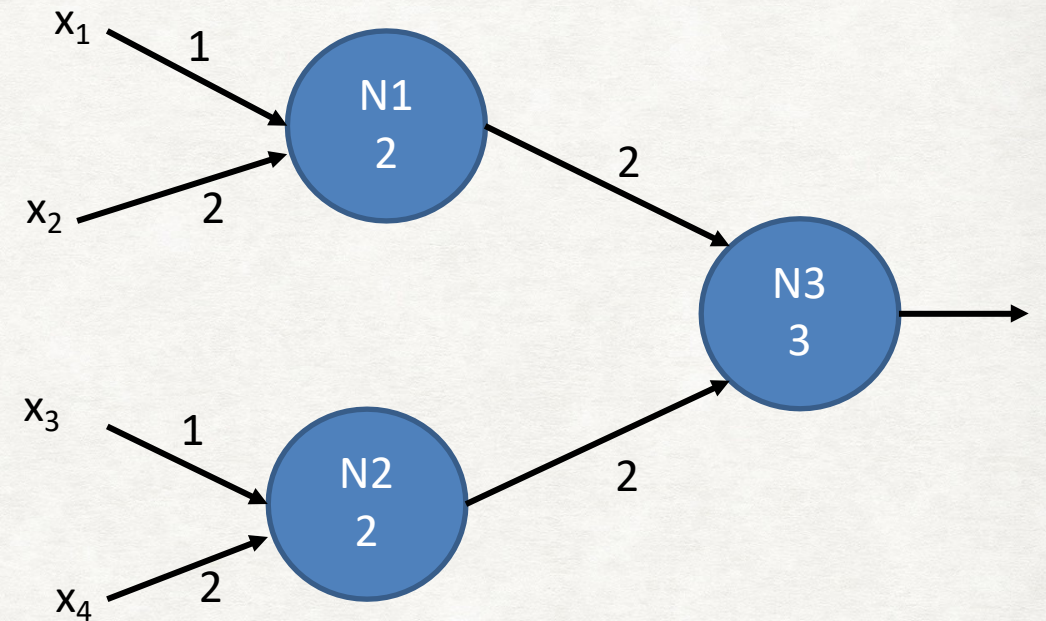
# LET'S DO AN EXERCISE.

In the given neural network, which combinations of input values cause node N3 to fire?

For N3 to fire, weighted input must be  $\geq 3$ .  
N1 must fire **and** N2 must fire.

For N1 to fire, weighted input must be  $\geq 2$ .  
Either  $x_2$  must be 1 or both  $x_1$  and  $x_2$  must be 1  
 $\langle x_1, x_2 \rangle = \langle 1, 1 \rangle$  or  $\langle 0, 1 \rangle$

For N2 to fire, weighted input must be  $\geq 2$ .  
Either  $x_4$  must be 1 or both  $x_3$  and  $x_4$  must be 1  
 $\langle x_3, x_4 \rangle = \langle 1, 1 \rangle$  or  $\langle 0, 1 \rangle$



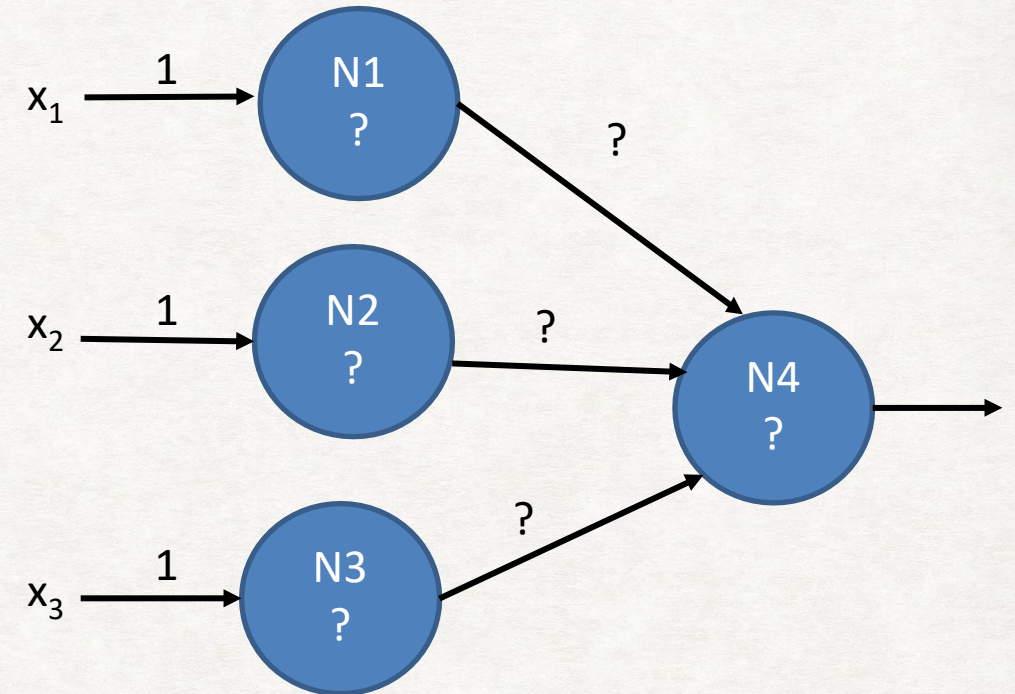
Therefore, for N3 to fire,  
the possible combinations of  $\langle x_1, x_2, x_3, x_4 \rangle$  can be:  
 $\langle 1, 1, 1, 1 \rangle$ ,  $\langle 1, 1, 0, 1 \rangle$ ,  $\langle 0, 1, 1, 1 \rangle$ ,  $\langle 0, 1, 0, 1 \rangle$



# LET'S TRY ANOTHER EXERCISE!

Assign weights and threshold values in the given neural network so that the output neuron fires only when  $x_1$  and  $x_3$  have the value 1 and  $x_2$  has the value 0.

Remember that weights can be negative.

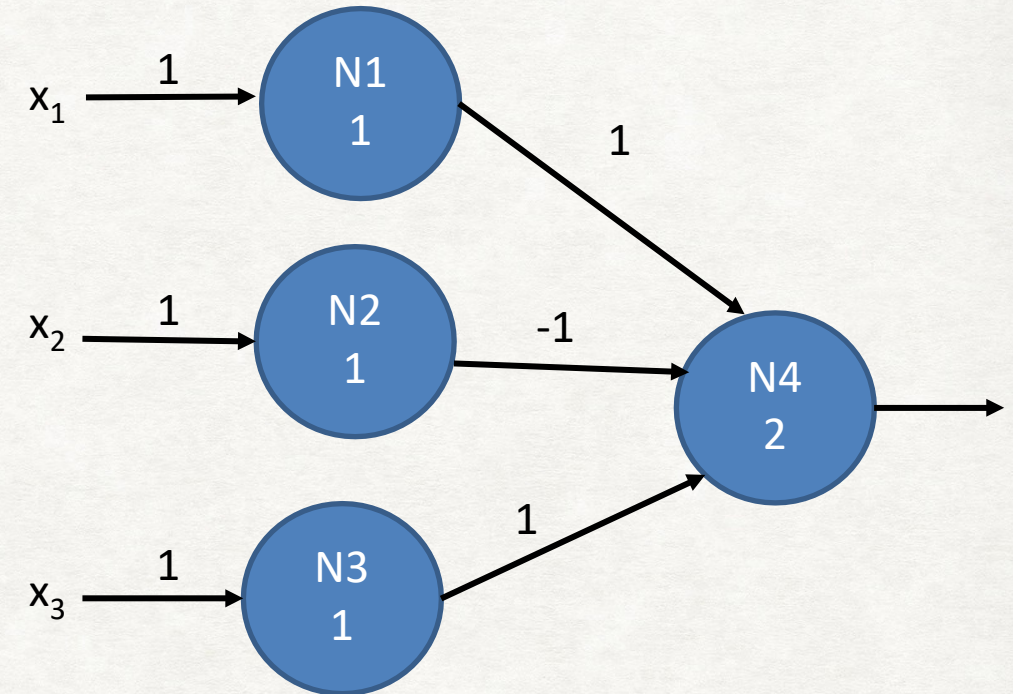




# SOLUTION - ANOTHER EXERCISE!

Assign weights and threshold values in the given neural network so that the output neuron fires only when  $x_1$  and  $x_3$  have the value 1 and  $x_2$  has the value 0.

Remember that weights can be negative.





# TO SUMMARIZE

Whether a neuron fires or not is a function of:

- The input values

- The weights on the inputs

- The firing threshold

Insight: Neurons with large weights on many inputs and a low firing threshold are more likely to fire than neurons with small or negative weights and a high firing threshold.

A weight of 0 for an input means that this input is effectively unused.